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THESIS

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DEPARTMENT OF THE AIR FORCE
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AFIT/GE/ENG/90D-08

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THESIS

Presented to the Faculty of the School of Engineering
of the Air Force Institute of Technology
Air University
In Partial Fulfillment of the
Requirements for the Degree of
Master of Science in Electrical Engineering

Mark Eugene Brown, B.S.E.
Captain, USAF

December, 1990

Approved for public release; distribution unlimited.

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Mark Eugene Brown

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Abstract

This study investigated the effectiveness of the Least Means Squared (LMS) algorithm against various types of common jammers. The LMS algorithm was originally developed by Widrow et. al. and was implemented using the Block Oriented Systems Simulator (BOSS). The LMS algorithm was inserted at the output of a two element antenna array. The array was configured so as to have one-half wavelength spacing. A quadrature hybrid signal structure was used. The array was then tested against a barrage and sweep jammer. The barrage jammer testing consisted of varying each of the three available jammer parameters; power, frequency and angle of arrival individually. The sweep jammer testing consisted of varying each of the three available jammer parameters; power, sweep frequency and angle of arrival individually.

The results of the simulation showed the LMS algorithm in combination with the quadrature hybrid was very effective against both the barrage and sweep jammers. It provided a 55 dB null in the barrage jammer cases and a 50 dB null in the sweep jammer case. Theses. (JH3)

Interference Cancellation in RF Signals
Using Adaptive Array Techniques

I. Introduction

1.1 Background

The interference of communication signals in the RF spectrum is a continually growing problem in military communications. The nature of this interference can be grouped into either intentional (e.g., jamming) or unintentional (e.g., commercial FM broadcast) interference. A receiving signal array is extremely vulnerable to the effects of this interference that we will term noise throughout this paper. The noise greatly reduces the ability of a communication system to reliably receive a desired signal by degrading the signal from its original waveform. The methods of eliminating these interfering signals are quite diversified and subject to the constraints of the system that it would be implemented upon. One such class of interference suppression techniques is the adaptive antenna, sometimes referred to as an adaptive array (4:1). An adaptive antenna has a controllable antenna pattern so that less energy is received in the direction of the interfering signal while simultaneously attempting to receive the maximum amount of energy from the desired signal. This optimizes the signal-to-noise ratio at the output of the antenna array. The antenna array is typically comprised of two or more spatially separated elements whose outputs are summed after being modified by a processing algorithm. Figure 1 represents the basic components of an adaptive array (10:11).

It is quite useful to separate a weak signal source from a strong interfering source so long as there is a spatial separation between the signal and interfering sources. Many of these algorithms produce a useful byproduct in their calculations,

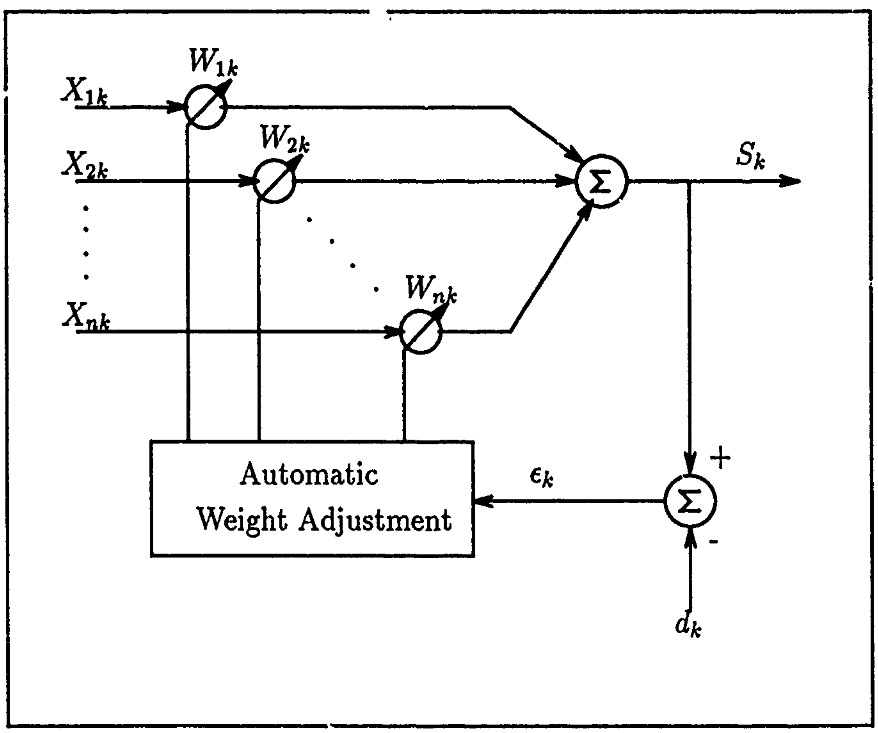


Figure 1. Adaptive Array Antenna

which is the angle-of-arrival (AOA) of each of the received signals. The AOA can be useful in determining the approximate location of the interfering and desired signal. Although the algorithms are quite different in their approach they are all hampered by the same constraint. That is, if there are N elements they will only be able to process $N-1$ interfering signals. One of these algorithms is the Least Mean Square (LMS) algorithm (12). It has been used quite extensively in the areas of control systems, interference suppression, and adaptive beamforming. The LMS algorithm is considered a classic adaptive algorithm and it is often used as a benchmark for newly developed algorithms of a similar nature. In the past it was not considered for applications requiring small power consumption and weight, due its computationally intensive requirements that would require a tremendous amount of processing power to operate effectively. Hence, there is little data concerning its performance against realistic jammer threats. With the advent of microminiaturized digital signal processors, it is feasible to operate such a system on a high-performance aircraft. While it is not difficult to fabricate and test these systems in a laboratory environment, it can be very costly to do so. In the case of an actual flight test on a high-performance aircraft, costly miniaturization would be required before testing with no guarantee of a successfully operating system.

1.2 Problem Statement

The performance of the Least Mean Square (LMS) algorithm has not been characterized against commonly encountered noise sources and, in particular, the type of jamming that a fighter aircraft might encounter in a hostile environment. If its performance could be simulated in a generic signal environment and that performance benchmarked, then other algorithms could be tested in turn against the same environment and compared. A method of developing and testing the performance of these algorithms in ground based simulation is required. One such simulation environment is the Block Oriented Systems Simulator (BOSS) (3). The Least Mean

Square algorithm will be researched and its attributes documented in preparation for its implementation and performance analysis upon the BOSS. An overview of how the LMS algorithm works and is implemented will be presented as well as its performance characterized.

1.3 Summary of Current Knowledge

1.3.1 Block Oriented Systems Simulator The Block Oriented Systems Simulator (BOSS) is a simulation environment developed for communication and signal processing applications (3). As the name implies, BOSS is a simulation environment for any application that can be represented by a hierarchical block diagram. Its basic functions include:

1. Graphical construction tools for system block development.
2. Time domain simulations.
3. Presentation of results in either the time or frequency domain.
4. Documentation of system block diagram design iterations.
5. Documentation of simulation results

After a block diagram is constructed, BOSS will generate the Fortran code necessary for the simulation. The premise of the BOSS is to allow the user to concentrate on the system problem definition, the analysis of the simulation results, and the resulting design modifications while freeing the user from the complexities involved with writing code for simulations.

1.3.2 LMS Adaptive Algorithm

1.3.2.1 Overview of Algorithm The Least Mean Square (LMS) algorithm was developed by Widrow, et al (12). The basic premise of the algorithm is to minimize the error between the output of the antenna array and some desired signal. The algorithm is able to operate without specific knowledge of either the angle-of-arrival of the signal we wish to receive or of the noise field. At the input to the array, the received signal is comprised of a transmitted waveform corrupted by an interference source. The input signal is then correlated with a desired signal model stored in the receiver. It may occur to the reader at this point, that if we have the desired signal to begin with then it would not be important to attempt to remove it from the noise. The desired signal model is not an exact replica of the received signal minus noise. It is some locally generated waveform with properties such that it is correlated with the received signal and uncorrelated with the interfering signal. This desired signal may be as simple as the waveform produced by the local oscillator in the receiver. An error signal is produced by subtracting the output of the array from the desired signal model. In referring back to Figure 1 it should be noted that the output of the array is based upon the summed output of each of the individual weight nodes. These outputs are formed by multiplying each input by the weight value that the LMS algorithm produces. These weights are created and thereafter adapted based upon the previous value of that weight added to the product of the error signal, convergence factor and array input as shown below.

$$\mathbf{W_{k+1}} = \mathbf{W_k} + 2\mu\epsilon_k\mathbf{X_k} \tag{1}$$

where,

$\mathbf{W}$ is the weight vector

k is the iteration

ϵ is the error signal

μ is the convergence factor

$\mathbf{X}$ is the input vector.

The convergence factor determines the stability of the algorithm and how quickly it will adapt to the optimal solution. The updated weight is based only upon the current error signal, current input signal and previous weight value. This allows for memory space reductions since only this one value, the previous weight, need be retained. In this manner the weights automatically update themselves and attempt to converge to an optimal solution. An optimal solution is one for which no additional adjustment of the weights provides any signal output improvement. At that point, the signal power is maximized while minimizing the interfering power. A detailed mathematical description of the LMS algorithm is contained in Chapter II.

1.3.2.2 Implementation of Algorithm The mathematical basis for the implementation is given by Widrow (13:99-114). He describes all the mathematical representations that are required for BOSS to effectively simulate the operation of the algorithm in conjunction with a realistic signal and processing environment. In the BOSS system, the algorithm will be represented by a block diagram of all the required components of an actual communication system and the antenna elements. The LMS algorithm requires only two multipliers, a gain factor and an integrator per channel use. These components can be combined to form the basic LMS loop and placed in any communication system that is similar in nature to the one in Figure 1. The LMS algorithm should require minimal effort to implement on the BOSS. The one area of debate is the proper choice of the desired signal model. The desired signal should be chosen so as to have the maximum amount of correlation with the signal that you intend to receive. Its choice will be one of the more important design tradeoffs in the LMS system implementation.

1.4 Assumptions

In order to reduce the complexity of the simulation and required computer time, the four element adaptive array will be treated as a stationary system. That is to say, it will have no spatial variations in its position over the time period of the simulation. This is a reasonable assumption considering a high performance aircraft will not be able to change its position, relative to the signal source angle-of-arrival, during the small time period of the simulation. The array will be implemented such that the element spacings are always at half-wavelengths no matter what the operating frequency. This is so that the antenna elements are always optimized regardless of operating frequency. It will further be assumed that all interference that is encountered by the system will be modeled by Additive White Gaussian Noise (AWGN) in nature to ease in the system analysis. The thermal noise, typically encountered in any electronic device, will be very small in comparison to the interference that is introduced into the system and thus will be ignored.

1.5 Scope

The adaptive array simulation that will be developed will duplicate the response of a two element adaptive array similar to the physical configuration of a linear array typically encountered in a high performance aircraft. The function of an AM transmitter will be developed . The function of the two different jammers will be developed so as to simulate a barrage and sweep jammer. These signal and jamming sources will be combined to produce a matrix formation of signal versus jammers for the simulation testing. The power levels of the signal will be varied while maintaining the same signal power level of the jammer, to produce different input signal-to-jammer ratios and then determine the output signal-to-jammer ratio for each case. The input signal-to-jammer ratio will then be plotted vs the output signal-to-jammer ratio. The convergence times of the algorithm will be determined for each power level. The data will be used to characterize the LMS algorithm after BOSS system verification.

1.6 Materials and Equipment

BOSS software is currently available to be used on the Digital Equipment Corporation (DEC) VAX workstation. The DEC workstation is located in the Signal

Information Laboratory at the Air Force Institute of Technology (AFIT).

1.7 Summary and Conclusions

The LMS algorithm described in this chapter is useful for the purpose of signal extraction from a noise environment. It can be used to counteract the effects of a directional interfering source so long as the interfering source and the desired signal are spatially separated. The LMS algorithm will converge to a maximum signal-to-noise ratio using an N element antenna array provided there are $N - 1$ signals present in the same bandpass of the receiver. The LMS algorithm can operate under changing signal and noise environment conditions by adaption of the weights that process the input signal from the antenna elements.

II. Theory

This chapter will serve to introduce the reader to basic adaptive filter theory as well as the properties of the LMS algorithm. The basic structure of an adaptive array will be presented. In addition, the signal characteristics of both the data signal and jammers will be discussed.

2.1 Adaptive Filter Theory

An adaptive system is one whose framework is altered or adjusted in response to contact with the environment it is functioning in. In essence, the adaptive array that is being described in this thesis may be considered to be a filter that has parameters that automatically adapt in response to some change in its environment. The basic adaptive system has the following general characteristics (14:4):

1. It can automatically adapt (self-optimize) in the face of changing (nonstationary) environments.
2. It can be trained to perform specific filtering and decision-making tasks.
3. It does not require extensive design procedures, it is essentially self-designing.
4. It can extrapolate its current training in order to cope with new conditions.
5. It can repair itself, in a limited manner, by adapting around system failures.
6. It is a nonlinear system with time-varying characteristics.
7. It is typically complex and difficult to analyze but offers increased system performance for signals whose input characteristics are unknown.

The single most important feature of an adaptive filter is its ability to be time-varying and self-adjusting in its performance. When a designer determines the structure of a desired filter, it is typically based upon some finite range of input

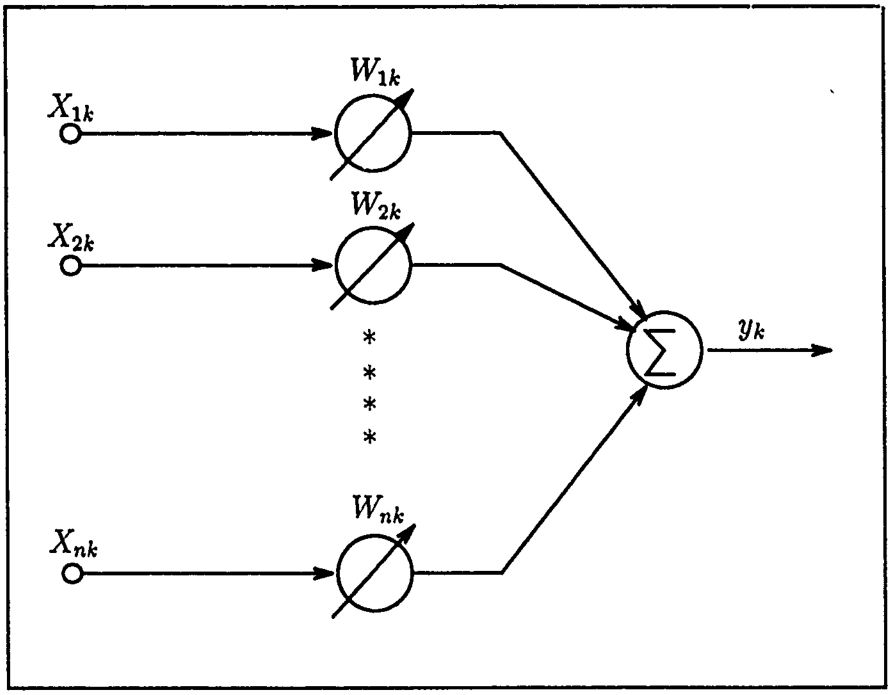


Figure 2. Basic Adaptive Linear Combiner

conditions that the system may encounter. There are many applications where the complete range of input conditions is not known and even if known may change in a time-varying nature. This is where the adaptive filter may prove the most useful. There are two features that readily distinguish them from any other type of nonlinear systems. First, the adaptive system is automatically adjustable in response to some time-average characteristic of the input signal. Second, these adjustments are made in such a manner so as to optimize a designated performance characteristic of the system.

The major component of an adaptive filter is the adaptive linear combiner as shown in Figure 2. In it you see the basic components of the linear combiner. The Input Signal Vector is the parallel input to the system, the Weight Vector is the values that are multiplied by the Input Signal Vector, and finally the Output Signal is the sum of the products of the Weight and Input Signal Vectors. The Input

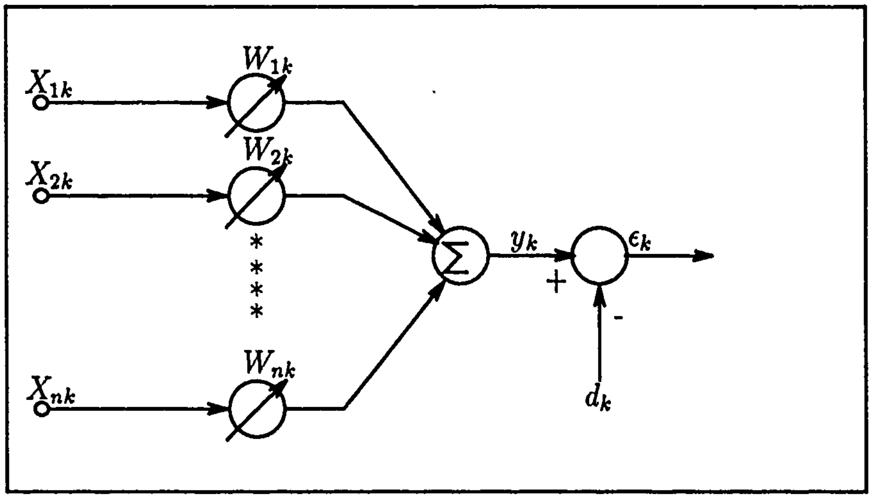


Figure 3. Adaptive Linear Combiner with Desired Signal and Error Signal

Signal Vector, Weight Vector, and Output Signal can be expressed mathematically as follows:

$$\mathbf{X_k} = [\mathrm{X_{0k}}, \mathrm{X_{1k}}, \ldots, \mathrm{X_{nk}}]^{\mathrm{T}} \tag{2}$$

$$\mathbf{W_k} = [\mathrm{W_{0k}}, \mathrm{W_{1k}}, \ldots, \mathrm{W_{nk}}]^{\mathrm{T}} \tag{3}$$

$$y_k = \mathbf{X_k^T W_k}. \tag{4}$$

As described previously, each Input Signal is multiplied by its corresponding Weight and then summed to form the Output Signal. It is the derivation of the weight value that is of major interest. Weight adjustment is the technique where the proper weight value is determined. The weight adjustment is determined by the systems output in comparison to some desired signal. This relationship is displayed in Figure 3. The resulting error signal is produced as the difference between the system output and the desired signal.

$$\epsilon_k = d_k - \mathbf{X_k^T W_k} \tag{5}$$

The error signal in Eq (5) is then squared to obtain the instantaneous squared error.

$$\epsilon_k^2 = d_k^2 - 2d_k\mathbf{X_k^T W_k} + \mathbf{W_k^T X_k X_k^T W_k} \tag{6}$$

The Mean Square Error (MSE) is obtained by taking the expected value of Eq (6) with the assumption that $\mathbf{W}$ is statistically stationary.

$$E[\epsilon_k^2] = E[d_k^2] - 2E[d_k\mathbf{X_k^T}]\mathbf{W_k} + \mathbf{W_k^T}\mathrm{E}[\mathbf{X_k X_k^T}]\mathbf{W_k} \tag{7}$$

We may now define $\mathbf{P}$ as the cross-correlation matrix and $\mathbf{R}$ as the autocorrelation matrix.

$$\mathbf{P^T} \equiv \mathrm{E}[\mathrm{d_k}\mathbf{X_k^T}] \tag{8}$$

$$\mathbf{R} \equiv \mathrm{E}[\mathbf{X_k X_k^T}] \tag{9}$$

Substituting Eq (8) and Eq (9) into Eq (7) gives us our performance surface.

$$\xi_k \equiv E[\epsilon_k^2] = E[d_k^2] - 2\mathbf{P^T W_k} + \mathbf{W_k^T R W_k} \tag{10}$$

If we look at Eq (10) as a quadratic function of the weight values, the error surface may be envisioned as a bowl. If the weights are changed we move to a different portion of the bowl. The adaptive process can then search the given performance surface in search of global minima or the bottom of the bowl which would indicate minimum error. The most common and successful method of performance surface search is by means of gradient methods. The gradient of the MSE is obtained by differentiating it with respect to the weight vector.

$$\nabla \xi_k = \frac{\delta}{\delta W}\xi_k = -2\mathbf{P} + 2\mathbf{R W_k} \tag{11}$$

When we have searched the gradient performance surface and have located the global minima then this will correspond to a optimal weight vector sometimes called the

Weiner weight vector.

$$W^* = \mathbf{R^{-1}P} \tag{12}$$

If we substitute Eq (12) into Eq (10) and simplify we can then determine the minimum MSE as shown below.

$$\xi_{min} = E[d_k^2] - \mathbf{W^{*T}P} \tag{13}$$

This is a very important result in that it relates the input signal vector to the minimum MSE that may be achieved using a adaptive linear combiner. The minimum MSE can also be expressed as

$$\xi_k = \xi_{min} + \mathbf{V_k^T R V_k} \tag{14}$$

where

$$\mathbf{V_k} \equiv \mathbf{W_k} - \mathbf{W^*} \tag{15}$$

and Eq (11) can be then rewritten as

$$\nabla \xi_k = 2\mathbf{RV_k}. \tag{16}$$

2.2 Least Mean Squared Algorithm

The Least Mean Squared (LMS) Algorithm is a method of searching the gradient performance surface and the primary one that will be addressed. It is one of the most popular methods due to its simplicity and computational ease. The development of the LMS algorithm begins with the gradient performance surface that was defined in Eq (11). In practice it is very difficult and computationally intensive to derive the exact gradient that may then be operated upon. It is therefore expedient to estimate the gradient using numerical methods of determining derivatives. This is accomplished using finite-time difference averages. The gradient performance surface or MSE may be estimated using this approach on the squared error term. This gives a gradient estimate for each iteration of the algorithm as

$$\widehat{\nabla\xi_k} = -2\epsilon\mathbf{X_k}. \tag{17}$$

This then becomes the method to perform weight adjustment in the following manner:

$$\mathbf{W_{k+1}} = \mathbf{W_k} - \mu\widehat{\nabla\xi_k}. \tag{18}$$

If Eq (17) is substituted into Eq (18), then the result is

$$\mathbf{W_{k+1}} = \mathbf{W_k} + 2\mu\epsilon_\mathbf{k}\mathbf{X_k}, \tag{19}$$

where μ is the gain constant that controls the speed and the stability of the adaption process. The fact that we have used an estimate of the gradient rather than the actual gradient implies that the iterative method will not produce exact responses to the system inputs. These responses will in fact produce variations in the weight values that are similar in nature to noise. This noise would imply that the descent in the gradient surface would not always follow the line of steepest descent in its search for the global minima. The noise effect upon the weight values is by no means negligible, but it does dampen with time as the adaptive process nears its optimal solution. In observation of Eq (19) it is clear that it can be readily implemented in a digital system with little complexity or complicated processing.

The determination of the gain constant μ is a subject of much research and debate. While a value that allows the system to operate is readily derivable, the manner of its determination in a real-time manner is not trivial. In order to insure that the system will converge to an optimal solution, remembering that optimal implies the minimum MSE that is not necessarily zero, the value of μ must fall within the region:

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{20}$$

where λ_{max} is the eigenvalue with the largest magnitude in the autocorrelation matrix $\mathbf{R}$. In order not to compute the eigenvalues of $\mathbf{R}$ it may be noted from matrix theory that the largest eigenvalue cannot be greater than the sum of the main diagonal in the matrix. We may then impose the slightly less restrictive conditions upon μ of:

$$0 < \mu < \frac{1}{tr[\mathbf{R}]} \tag{21}$$

where $tr[\mathbf{R}]$ is the sum of the diagonal elements of $\mathbf{R}$. This is still computationally difficult to produce. If we look at Eq (9) we can see that sum of the diagonal elements in $\mathbf{R}$ is (L+1) times the expected value of the input value to each filter squared. In other words, (L+1) times its signal power where L is the number of taps in the adaptive filter. Eq (21) then becomes

$$0 < \mu < \frac{1}{(L+1)(signal\ power)} \tag{22}$$

This constraint is more readily applied since the input signal power is quite easy to compute. This gives us a range of values for μ that may be used in the adaption process but it is desirable to determine a better method for its determination within this range. The excess MSE is defined as the expected value of the difference between the current MSE and the minimum MSE. The misadjustment of the process is defined as the ratio of the excess MSE to the minimum MSE. The misadjustment of a process is sometimes referred to as the "cost of adaption" in that it is a figure of merit for how closely the process tracks the Weiner solution. The misadjustment of the system can approximated by:

$$M \approx \mu \cdot tr[\mathbf{R}] \tag{23}$$

and if we solve Eq (23) for μ we arrive at:

$$\mu \approx \frac{M}{tr[\mathbf{R}]} \tag{24}$$

The same development that was used to derive Eq (22) from Eq (20) can be applied here also to produce:

$$\mu \approx \frac{M}{(L+1)(signal\ power)}. \tag{25}$$

We now have a working approximation for determining the value of μ based upon the input signal power, the number of taps in the adaptive filter, and the misadjustment. A problem arises when we have a input signal with varying instantaneous power. If the value of μ is too small for the input power the weights will never converge due to the slow search of the gradient. If too large a value of μ is chosen, then the system will become unstable and nonconvergent. A method is desired that measures the incoming signal power and accordingly adjusts μ to meet the criteria of Eq (24). This can be accomplished by taking the sliding window average of the input signal squared so that its average is obtained over a finite period of time. This averaging represents the systems average power over the time of the window and prevents the system from reacting to large changes in power that may only be input spikes. The misadjustment is typically set to 10 percent in most applications with satisfactory performance (13).

This method of determining μ given in Eq (24) is quite efficient for producing the value of μ that is overdamped (14:50). It will produce appropriate weight values that will converge to the optimal solution will little or no overshoot. It is possible to set the system convergence to other dampings if desired. The system will be stable if the criteria of Eq (21) is observed. This corresponds to $0 < M < 1$ for stability, $0 < M < 0.5$ for overdamping, $M = 0.5$ for critically damping, and $0.5 < M < 1$ for underdamping. The performance of the LMS loop is totally dependent upon the system input. As was shown in Eq (24) the system will have a smaller time constant in response to increased signal power. If the time constant is lessened, then the system bandwidth will increase. Hence the system bandwidth is directly proportional to the input signal power. The higher the signal power, the larger the feedback gain and the quicker the system responds. It has been noted that faster adaption leads to a more noisy response (underdamping). It is then apparent that if best steady state response is the overall goal of the process then the system must therefore adapt slowly (overdamped). This is readily attained when the systems input signals are stationary in a statistical sense. This becomes more difficult when the input signals statistics are of a time-varying nature (13). It then becomes necessary to compromise between small values of μ for fast adaption and tracking of the changing signal characteristics and larger values of μ for control of the noise in the weight vectors. If we go back to the analogy of the error surface being a sort of bowl that we wish to find the bottom of, then we may now extend the analogy to the nonstationary case. In the stationary case the bowl sat in a fixed position and was systematically searched for its bottom. In the nonstationary case the bowl is now moving and changing its shape so that its minima is never in the same position or has the same value. This makes it necessary to have the value of μ vary as the system performance surface changes shape as in Eq (25).

2.3 Adaptive Array Structure

An adaptive array is comprised of a set of sensors whose outputs are combined in such a manner so as to produce a desired effect. This desired effect is typically a beam that is looking towards some desired signal while shielded from any undesired signal such as a jammer. A typical two element adaptive array is shown in Figure 5. As you can see this is very similar to the linear combiner that has already been discussed. The only major difference is that the input from each antenna element is split into an in-phase and quadrature signal so that two weights are needed for each input element. The goal of the adaptive array is to be able to distinguish between

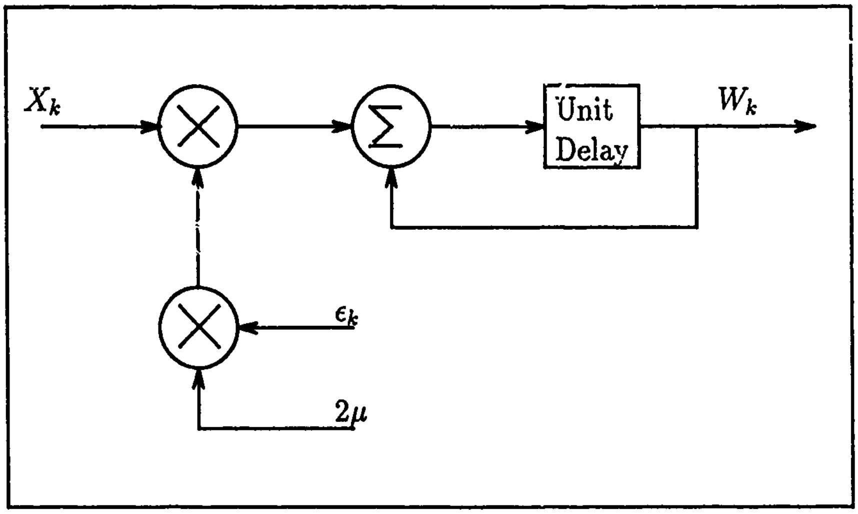


Figure 4. Functional Diagram of LMS

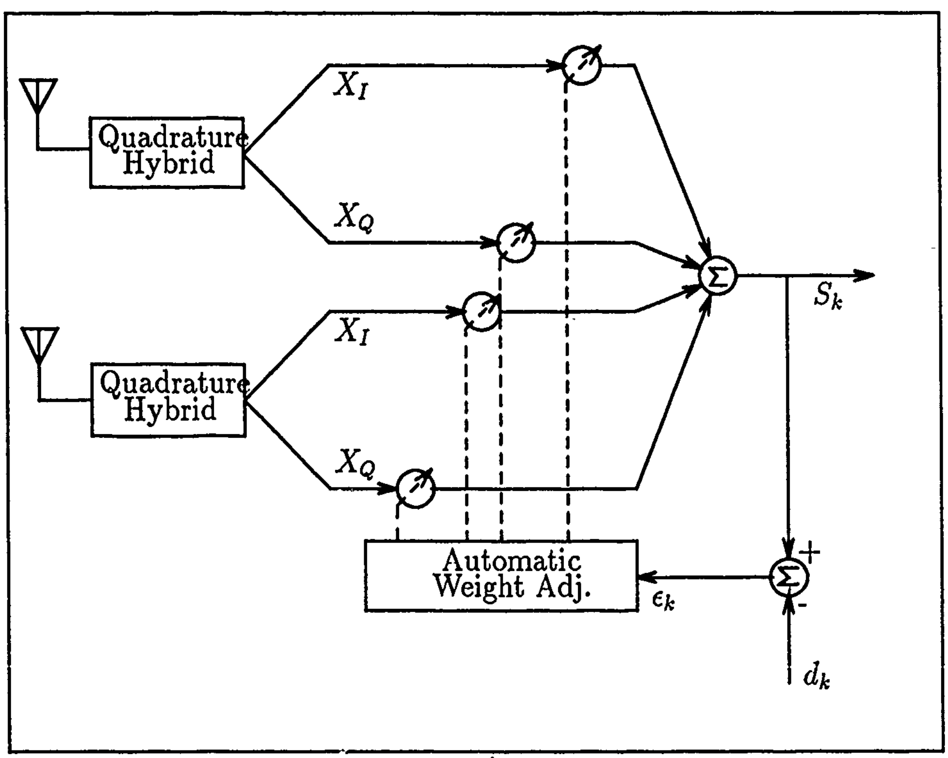


Figure 5. Two Element Quadrature Array With Steerable Beam

a desired and undesired signal. It may then automatically adapt the antenna beam in such a manner so as to maximize the desired signal power while minimizing the undesired signal power. This may be accomplished using any number of different control algorithms. Some of the more popular ones are the minimum noise variancc criteria (2), the minimum mean-square error criteria (9), the maximum likelihood criteria (7), and the maximum signal-to-noise ratio criteria (1). The LMS algorithm has gained a rather large popularity in recent years due to its simplicity in computation and its effectiveness in so many varying applications. The basic underlying premise in all these algorithms is the a priori knowledge of some facet of the signal environment. This may be the signal's angle-of-arrival or a close approximation of the signal itself. Thus if a close approximation were available then the system could control its own pattern.

2.4 Input Signal Characteristics

2.4.1 Data Signal The input signal can be any standard modulation type that contains data that is easily analyzed. This is so it may be determined if the data is corrupted by the interference that it encountered. It is desirable that it be of a narrowband nature. This is so that experiments may be performed comparing interference with a similar narrow bandwidth with that of interference with a wide bandwidth. To satisfy these requirements a psuedorandom sequence modulating large carrier AM was chosen. The data rate of the sequence was selected to be a tenth of the carrier frequency.

2.4.2 Jammers The jammer is a major portion of a military forces electronic warfare systems. The term electronic warfare is defined as (5):

> Electronic Warfare is military action involving the use of electromagnetic energy to determine, exploit, reduce, or prevent hostile use of the electromagnetic spectrum and action which retains friendly use of the electromagnetic spectrum.

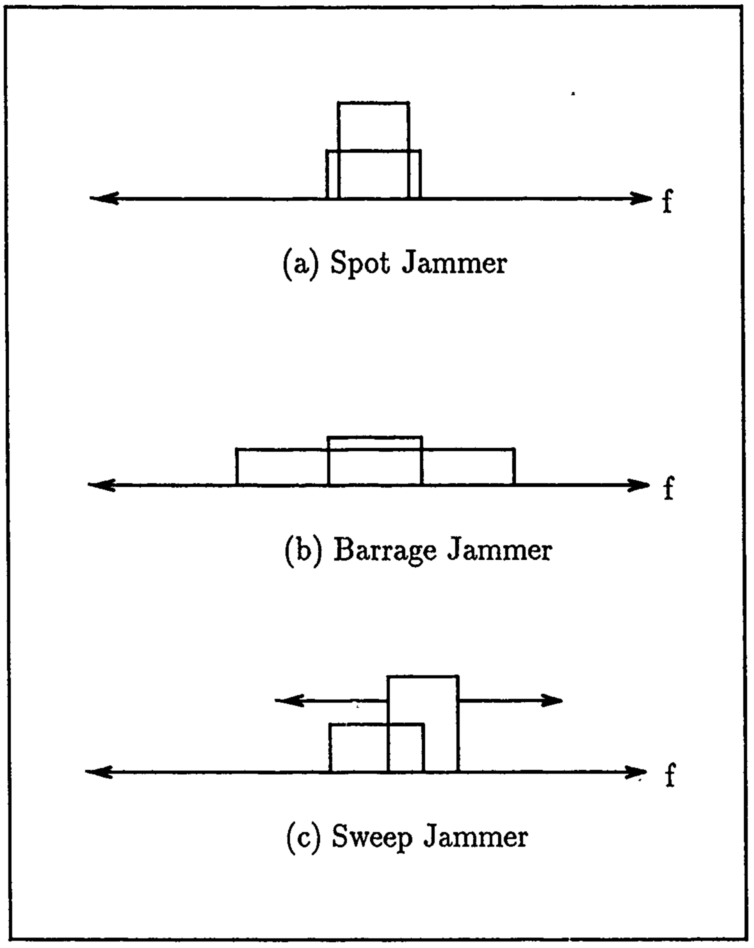


Figure 6. Frequency Spectrum of Different Jammer Types

There are three major types of jammers: the spot jammer, the barrage jammer, and the sweep jammer (6:88-91). The spot jammer concentrates all its power in a single narrow bandwidth so as to overwhelm the target system with much larger power output. The barrage jammer spreads its power output over a much wider bandwidth, typically on the order of ten percent of the center frequency. And lastly, the sweep jammer is again a narrow bandwidth transmission very similar to the spot jammer, that varies its center frequency or sweeps its power along the target bandwidth. These jammers frequency spectrum are illustrated in Figure 6.

The use of the spot jammer is typically constrained to certain high-value targets in a one-on-one type situation where there is one jammer and one emitter. It attempts to overwhelm the target emitter and restrict its effectiveness completely. It can have any number of modulation types but is typically narrow-band FM. The ideal situation is to have the bandwidth of the spot jammer identical to that of the target system. The barrage jammer is used to cover a large range of frequencies so that it may jam many target emitters simultaneously. Its modulation type is typically bandlimited AM. As stated previously its bandwidth is spread over ten percent of its center frequency. The sweep jammer is used to concentrate a large power output over a narrow bandwidth but not restricting its application to a single target but sweeping over a range of frequencies in order to disrupt operations on a periodic basis. Its modulation type is typically narrow-band FM.

The concentration of experimentation will be on the barrage and sweep jammers. This will highlight the effectiveness of the LMS algorithm with a wideband signal, the barrage jammer, and a nonstationary narrowband signal, the sweep jammer.

III. Implementation

This chapter will discuss how each of the desired functions that we wish to simulate is implemented. In order to implement a system simulation, a simulation environment is required. The environment chosen was the Block Oriented Systems Simulator (BOSS) and a brief overview of it is given. The remainder of the chapter is devoted to the implementation of the system in BOSS. The construction of the LMS loop, data signal, jammers, and receiving system is detailed and their BOSS representations depicted.

3.1 Block Oriented Systems Simulator

The foundation of any simulation of a communication system analysis is the simulation environment. Computer system analysis falls into two general categories. The first is the formula-based approach in which the computer evaluates complex mathematical representations that the engineer inputs. The second is the simulation-based approach in which the computer is used to simulate actual components and their interaction with each other. The Block Oriented Systems Simulator (BOSS) falls into this second category. The BOSS is designed for the engineer who may have little or no experience in computer operations or simulation generation. This does not detract from it being a very robust simulation environment suitable for the most complex simulations of communication systems. It is a complete simulation environment for the design and analysis of any system that can be modeled with block diagrams which represent signal processing operations.

The simulation-based approach has four basic steps in BOSS. The first is to represent the system with block diagrams. The second is to generate samples of the input signals. The third is to perform the signal processing operations. The fourth is to store the resulting waveforms for analysis. In the BOSS environment the engineer inputs the system block diagram using a mouse-driven graphics oriented toolbox of standard signal processing modules to assemble the desired system representation. If the desired process is not present in the toolbox and cannot be constructed by a combination of the available processes, then the engineer may construct his own process using FORTRAN code. In practical applications this was not found necessary to do, as the toolbox is very complete. After the desired system is constructed and saved, the engineer is relieved of the responsibility of any further generation of results. The BOSS will take care of the code generation, execution and presenting the results of the simulation, allowing the user to concentrate upon the design and analysis of the system. Once the system is saved the user can recall it from the BOSS database and perform the desired simulations upon it. The user first attaches probes at any connecting point on the system block diagram. These probes serve to tell BOSS to store the generated waveforms from these points. The user then will input the parameters of the simulation (e.g. simulation duration, frequency of operation, sampling time etc.) and directs BOSS to undertake the simulation. BOSS will then generate the FORTRAN code necessary to represent the system and the simulation parameters. Once it completes the code generation it will execute the program and inform the user of its completion. The time to complete a simulation is very difficult to judge, but is based primarily upon the system complexity, number of probes, sample time and length of simulation. Upon completion of the simulation the results are available for analysis in either the time or frequency domain. The user selects a probe that he wishes to study from a menu and the method of presentation. These commands and all others in the BOSS system are selected from a series of pop-up menus that have all the BOSS functions represented. This has been a very brief and incomplete overview of the BOSS. For further data the reader should refer to the Block Oriented Systems Simulator (BOSS) Users Guide (3).

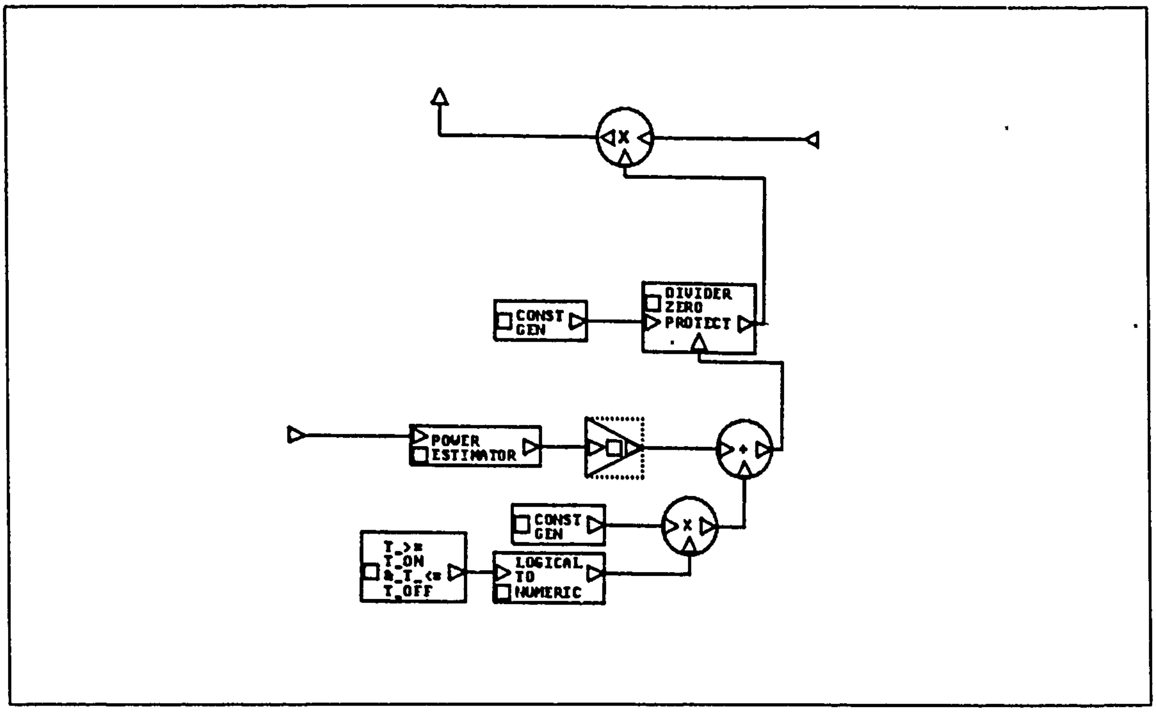


Figure 7. μ Estimator Module

3.2 LMS Module

The development for the Least Mean Squared (LMS) algorithm was given previously in Chapter II. The implementation of the LMS algorithm followed that development exactly. The way that BOSS is structured makes it very straight forward to implement any system that has a mathematical model. The model in this case is Eq (19)

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu\epsilon_k\mathbf{X}_k \tag{26}$$

As was previously discussed in the development of LMS it is necessary to also have some method to adapt the value of μ to the changing input signal power. This is accomplished via the μ estimator module shown in Figure 7.

The signal to the left of the figure is the input signal $\mathbf{X}_{k-1}$, the input signal to the right of the figure is the error signal ϵ_{k-1}, and the output signal at the top of the figure is $\mu_{k-1}\epsilon_{k-1}$. The power estimator outputs the average instantaneous

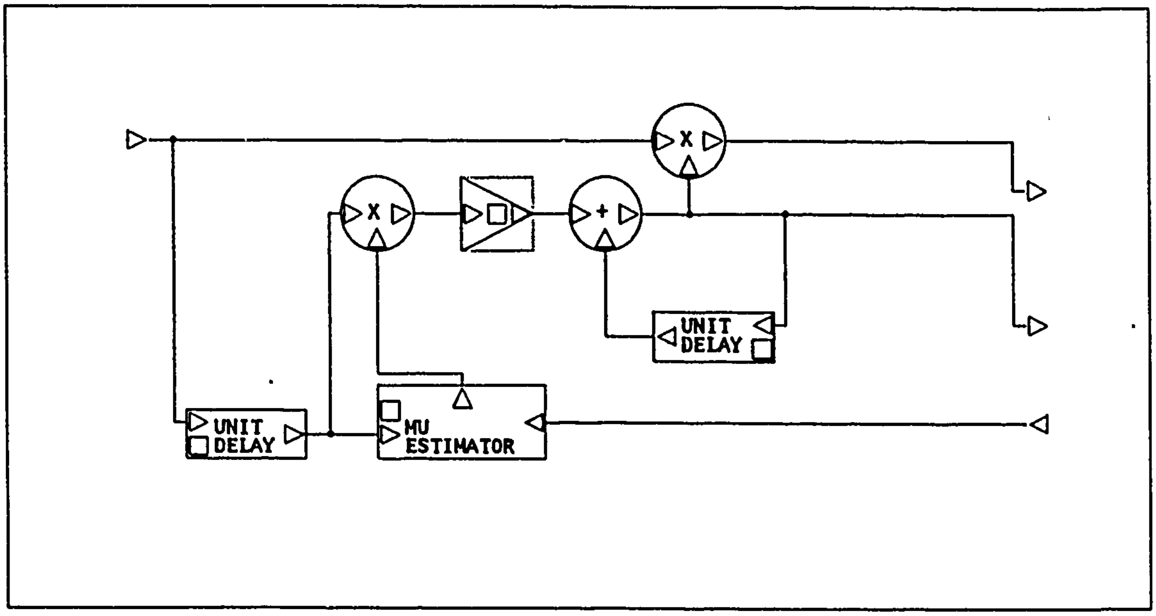


Figure 8. Least Means Squared Module

power of the input signal over ten samples. It is then added to a very small constant value to insure that at any one time there is never a zero output power. This is very important in the system because you may have an unstable system at the very beginning of a signal input. The constant generator allows the experimenter to input a value of M (the misadjustment) to the system. This is then the current value of μ that the system will then multiply by the error signal. This module is then inserted into the LMS module that is shown in Figure 8.

The signal to the left of the figure is the input signal X_k and the input signal to the right of the figure is the error signal ϵ_{k-1}. The output signal on the lower right of the figure is the current weight value W_k and the output signal at the upper right of the figure is the output signal y_k. It has been already been stated that the output of the μ estimator is the term $\mu_{k-1}\epsilon_{k-1}$. This is then multiplied by the X_{k-1} term. The amplifier at the output of the multiplier then produces a gain of two. The product is then added to the previous value of the weight value W_{k-1} to produce the next weight value according to Eq (19). This is then multiplied by the input signal

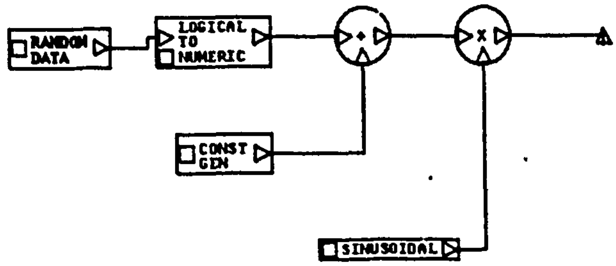


Figure 9. Data Signal Module

and the product is the output signal y_k.

3.3 Data Signal Module

The Data Signal Module is composed of a large carrier AM transmitter with a random data generator as its input. Its block diagram is shown in Figure 9. The random data generator produces a logical stream of random data based upon an input seed number. It was necessary to convert this logical stream to numeric values by the conversion module shown in the figure. The constant generator outputs a value of one to be added to the random data giving the desired large carrier AM effect. It is constructed in such a manner so as to have constant transmitter power with the only output power fluctuations being as a result of the input data's change in amplitude.

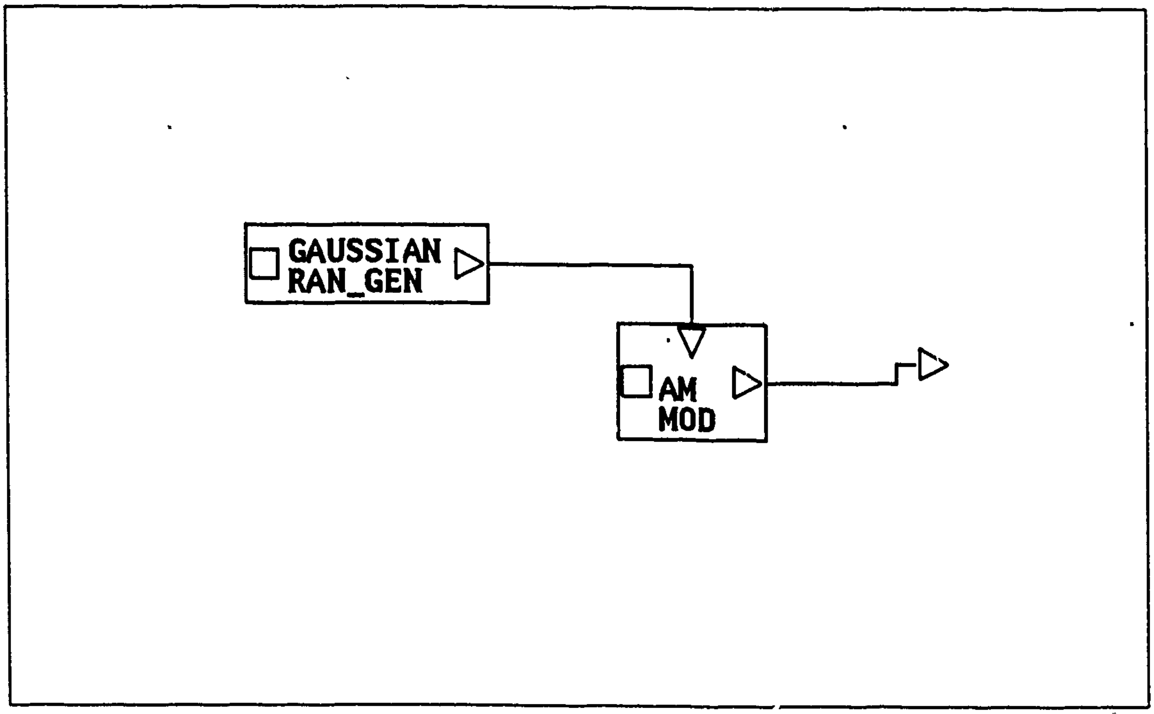


Figure 10. Barrage Jammer Module

3.4 Barrage Jammer Module

The Barrage Jammer Module consists of a gaussian distribution random data generator input to a large carrier AM transmitter whose output is bandlimited to ten percent of the center frequency. It is represented in Figure 10. The gaussian random data generator has a zero mean and unit variance output distribution and is also initiated by a seed number. The AM transmitter is the same as in the Data Signal Module. The output bandpass filter is a third order butterworth with 3 dB attenuation at the edge frequency. The module is constructed so that the edge frequency of the bandpass filter is automatically set to produce a bandwidth that is ten percent of the center frequency.

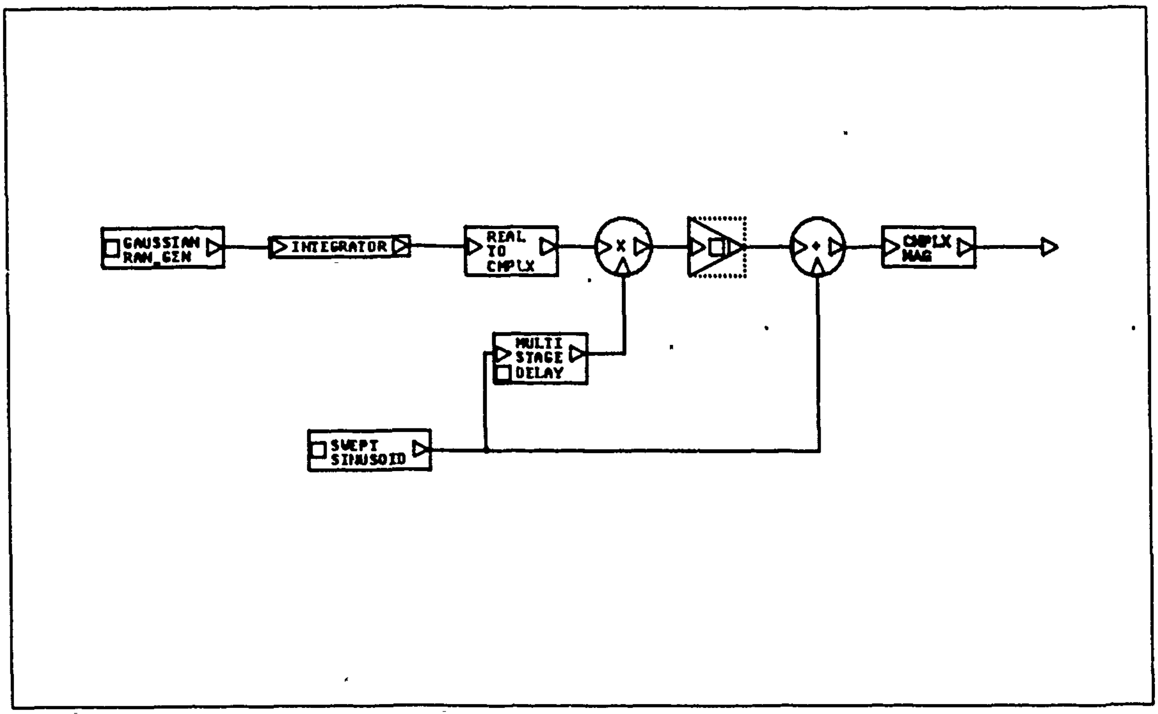


Figure 11. Sweep Jammer Module

3.5 Sweep Jammer Module

The implementation of the Sweep Jammer module took a more complex turn than was desired and there are some slight abnominalies that require noting. As was described earlier the standard sweep jammer consists of a gaussian noise source input into a narrowband FM transmitter. The narrowband FM transmitter has as its local oscillator a swept sinusoid instead of a constant value sinusoid. This allows for the system to vary its center frequency according to the swept rate of the oscillator. The implementation is shown in Figure 11. The system that was implemented behaves in the manner of a narrowband FM transmitter once a sufficient number of samples of the swept sinusoid are produced and sent through the multi-stage delay module. The multi-stage delay represents the Hilbert transform that is required of a FM system. Until this occurs the output signal is of a pure sinusoidal nature only with no noise contained in it. This did not appear to affect the results and will be discussed further in Chapter V.

3.6 Antenna Array Module

The Antenna Array Module is utilized to form the necessary time delays in order to simulate the incoming signals angle-of-arrival (AOA) and sum them to form two antenna elements that are spaced a half-wavelength apart. This delay can be approximated by the equation shown below if the transmitter is in the far field so that it can be assumed that the incoming AOA for each element is equal.

$$\phi = \pi \sin(\theta_D) \tag{27}$$

This phase delay can then be introduced as a time delay so long as the signals are of a finite nature. In other words, the signal must have a beginning point and an ending point. Once again the time delay is implemented using the multi-stage delay module. The AOA of the signal (either a data signal or a jammer) can be computed according to the following equation.

$$\theta_D = \arcsin(2 f_o T_s N) \tag{28}$$

where,

f_o is the operating frequency

T_s is the sample time

N is the delay (an integer value)

This is then replicated for each of the input signals and summed to form the output of each element as shown in Figure 12.

3.7 Complete System Module

The Complete System Module is composed of the modules already described as well as basic modules from the BOSS toolbox. It implements a two element array with quadrature outputs that, after LMS adaption, are summed to form the system output as shown in Figure 13. The system was implemented to receive a data signal

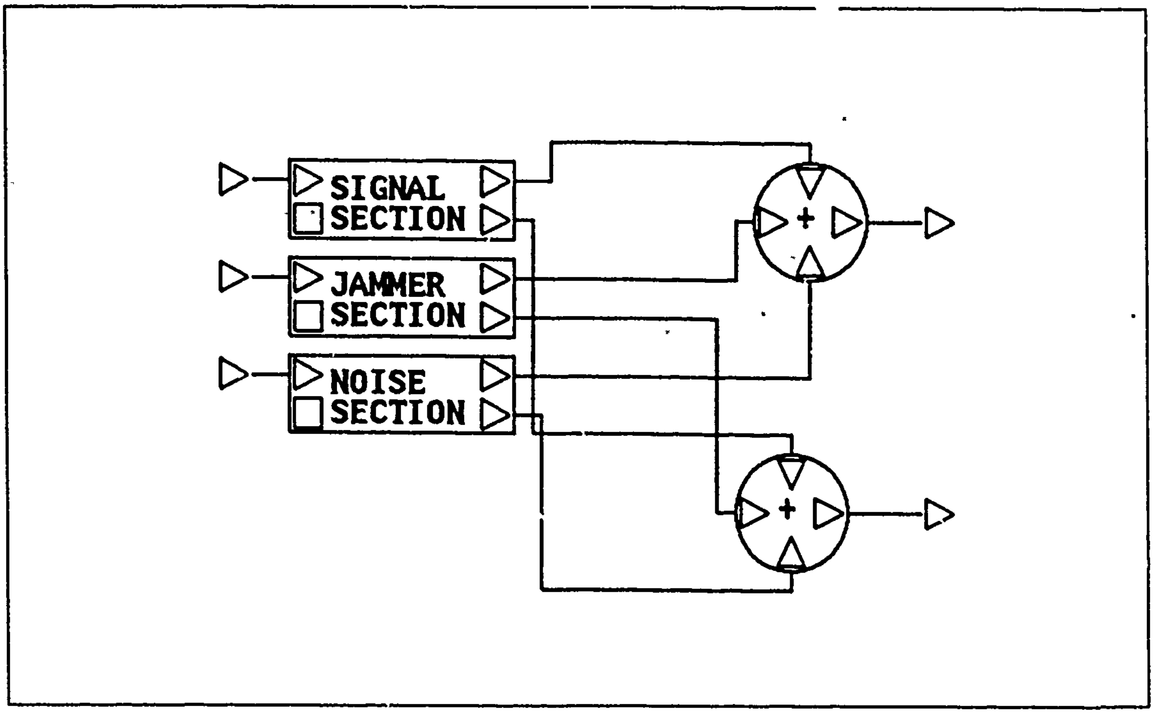


Figure 12. Antenna Array Module

and two jammers into the two element array. Their individual delay times are then calculated and impressed upon the signal. Each element output is then broken into its quadrature output and fed into an individual LMS loop. As was discussed in the LMS module section it has two inputs and two outputs. The two inputs are the input signal and the error signal. Its two outputs are the adapted signal and the weight value. Each of the four adapted signals are then summed to form the system output. The system output is then inverted and compared to the desired signal in order to generate the error signal that each of the individual LMS loops uses. The system output is also sent to a envelope detector to determine the effects of system adaption on the output and compared to the unprocessed output from the first element of the array.

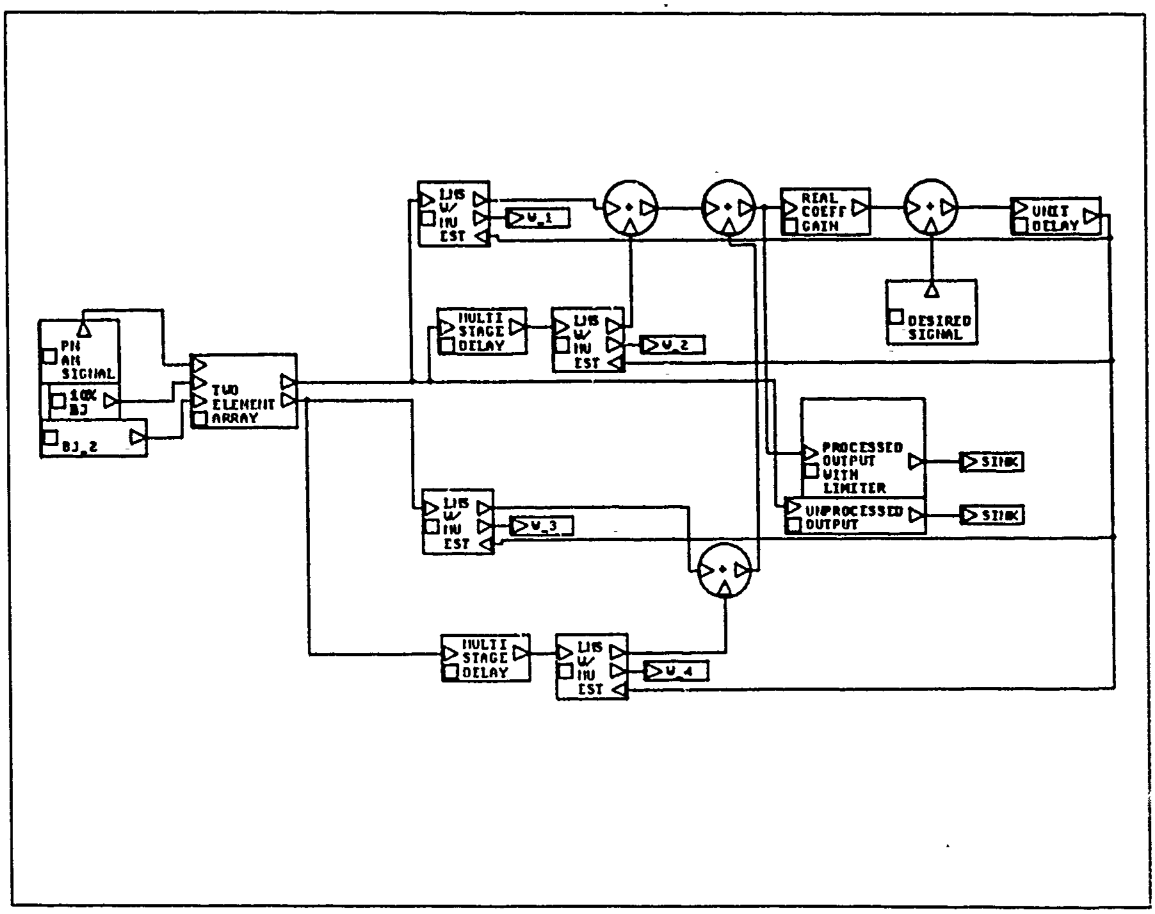


Figure 13. Two Element Adaptive Array

IV. Methodolgy

This chapter will introduce the reader to the experiments that were performed in order to characterize the performance of the LMS algorithm in a two element array. The experiments fall under two major headings, wideband and narrowband jammer experiments. The LMS algorithm and the associated two element array have been implemented on the Block Oriented Simulator System (BOSS). The parameters of the simulations will be discussed and a guide to determining appropriate values to be input will be provided. This discussion will facilitate any further experiments that the reader may wish to perform.

4.1 Wideband Experiments

The wideband experiments were those that involved the use of the wide bandwidth barrage jammer and a single data signal. They were broken into three major cases. The constant frequency and variable power case, the variable frequency and constant power case, and the constant frequency, constant power with variable angle-of-arrival (AOA) case were each performed. The three cases that are presented are intended to represent the majority of the interaction cases between a barrage jammer and a transmitter. Each case involved the execution of numerous simulations in order to acquire the necessary data to produce performance charts of the algorithm. In each case it was necessary to gradually vary some parameter of the simulation in order to determine the output signal power and the number of iterations required to converge.

4.1.1 Constant Frequency and Variable Power Case The wideband experiments had two signal inputs, a barrage jammer and a modulated data signal. This experiment explores the effects of the input signal-to-jammer ratio (SJR) on the figures of merit (output SJR and iterations to converge). The angle-of arrival (AOA) of the jammer was set to 30 deg while the AOA of the data signal was 0 deg. The frequencies of the data signal transmitter and the barrage jammer center frequency were set to the same value. This centered the barrage jammers frequency spectrum over the data signals spectrum. This allowed for the power of barrage jammer to be applied equally to all the components of the data signal frequency spectrum. The barrage jammer output power was set by fixing the amplitude of the modulating sinusoid with its only power variations being in the gaussian random data that is input into the AM transmitter. Its average power over the duration of the simulation was recorded and used in all calculations concerning this case. The amplitude of the data signal was then set to a constant value and the simulation was executed. When the simulation had completed its execution the average input signal power, average input jammer power, average output signal power, and number of iterations to converge were recorded. This same data was collected for all the experiments. The simulation was then set to the same parameters as in the previous run but with a slightly lower input data signal power. This process was repeated until the input signal power was lowered to the point that the loop could not converge to an optimal solution.

4.1.2 Variable Frequency and Constant Power Case The previous experiment was then configured for a fixed input power and varying barrage jammer center frequency. The angle-of-arrival (AOA) of the jammer was again set to 30 deg while the data signal AOA was 0 deg. The power of both the barrage jammer and the data signal were set to a fixed value. This is done to determine the effects of the barrage jammers frequency spectrum positioning over the entire spectrum of the data signal. The offset of the center frequency of the barrage jammer from the data signal frequency would allow for some spectral components of the data signal to be received with less jammer power than others. The center frequency of the barrage jammer was varied from eighty to one hundred and twenty percent of the data signal transmission frequency.

4.1.3 Constant Frequency and Power with Variable AOA Case The power of the input signals were once again set to a constant value as in 4.1.2. The frequencies of the jammer and the data signal were the same as in 4.1.1. The AOA of the data signal was once again set to 0 deg while the AOA of the jammer was varied from 0 deg to 90 deg. This serves to show the impact on the performance of the algorithm when the signals have a spatial separation.

4.2 Narrowband Experiments

The narrowband experiments involved the use of the narrow bandwidth sweep jammer and a single data signal. They were broken into three major cases. The constant sweep frequency and variable power case, the variable sweep frequency and constant power case, and the constant sweep frequency, constant power with variable angle-of-arrival (AOA) case were performed. The three cases that are presented are intended to represent the majority of the interaction cases between a sweep jammer and a transmitter as in the wideband experiments. The compilation of data was performed in much the same manner as the wideband experiments.

4.2.1 Constant Sweep Frequency and Variable Power Case This experiment explores the effect of varying the input SJR on the figures of merit (the output SJR and iterations to converge). The sweep frequency of the jammer can be set to any desired value. As a rule of thumb, the typical value for normal operation is ten percent of its center frequency. That center frequency was set to the frequency of the data signal so that the jammer would constantly pass through the frequency spectrum of the data signal. The angle-of-arrival (AOA) of the sweep jammer was set to 30 deg while the data signal AOA was 0 deg. As in the wideband experiments, the jammer power was fixed while reducing the data signal power until convergence was not possible.

4.2.2 Variable Sweep Frequency and Constant Power Case This case investigates the effects of varying the sweep rate of the jammer on the figures of merit. The angle-of-arrival (AOA) of the sweep jammer was set to 30 deg while the data signal AOA was 0 deg. The output power of the jammer and the data signal were fixed and a low value of sweep rate was input into the simulation (one percent of the center frequency). The sweep rate was then increased up to twenty percent of the jammers center frequency and the figures of merit recorded.

4.2.3 Constant Sweep Frequency and Power With Variable AOA Case This case investigates the effects of changing the angle-of-arrival (AOA) of the sweep jammer on the figures of merit. The AOA of the data signal was once again set to 0 deg while the AOA of the jammer was varied from 0 deg to 90 deg. The jammer and data signal power were held to constant values and the sweep rate of the jammer was once again set to ten percent of the center frequency.

4.3 BOSS Operation

This section will describe in detail the method to determine the proper value of the various input parameters for the two models. This is done to facilitate verification of the results that will be presented in the next section. It is also done so that further experimentation can be performed with a minimal learning curve on the BOSS model.

4.3.1 Barrage Jammer Model There are fourteen parameters that must be determined and input before the BOSS will execute a simulation. In this section the manner that was used to determine these parameters will be discussed. The parameters will be discussed in order of appearance on the BOSS Set Parameter window. The first parameter is the Stop Time. This tells BOSS the duration of the simulation in seconds. The experimenter should use care in selecting the length of the simulation as it has a direct bearing on the number of samples taken. If the value is too large the simulation will consume more disk storage than is necessary. The next parameter is DT, which is the BOSS terminology for sample time in seconds. This value is subjective but for proper sampling with no aliasing it is recommended that it be set to a tenth of the period of the data signal. The BJ-2 AMP and BJ-1 AMP are the amplitude of the modulating sinusoid for the AM transmitters in the barrage jammers. The BJ FREQ is the center frequency of the barrage jammer. This parameter sets the frequency for both of the barrage jammers in hertz. The AM AMPL sets the amplitude of the modulating sinusoid for the AM transmitters in the data signal. The DATA RATE sets the bit rate of the random data input into the AM transmitter. It is suggested that this be set to no more than thirty percent of the transmission frequency. The OUTPUT LIMIT sets the ceiling of the soft limiter in the envelope detector. This should be set to one. The FREQ parameter determines the frequency of operation for the data signal in hertz. The MISADJUSTMENT parameter is one that was discussed at some length in Chapter II. It may be set to any value between zero and one, but 0.1 is recommended. The 1/4 X F X DT parameter is one quarter of the product of the FREQ parameter and the DT parameter. This should be an integer value and it determines the amount of delay for the quadrature elements of the array. The SIGNAL DELAY parameter (N) sets the AOA of the data signal according to the relationship

$$N = \frac{\sin(\theta_D)}{2 \cdot FREQ \cdot DT} \tag{29}$$

where,

θ_D is the AOA of the signal

FREQ is the operating frequency

DT is the sample time

In the same manner the BJ-1 and BJ-2 DELAY's are determined for each of their AOA's.

4.3.2 Sweep Jammer Model The Sweep Jammer Model is set up in a similar manner to the Barrage Jammer Model and many of the parameters that were previously discussed remain the same. In this section the additional or different parameters will be discussed. The HZ/VOLT JAMMER SWEEP determines the sweep rate constant of the jammer or the number of hertz deviation per volt input. The input is a one volt sinusoid whose frequency is determined by the JAMMER SWEEP RATE parameter. These two parameters control the bandwidth of the sweep jammer (two times the HZ/VOLT JAMMER SWEEP parameter) and how quickly it sweeps through that bandwidth (JAMMER SWEEP RATE). The BJ-1 DELAY controls the AOA of the Sweep Jammer. All other parameters are as described in the previous section.

V. Experimental Results

This chapter will presents the results of the experiments described in Chapter IV. There were approximately forty simulations run for each experiment, for a total simulations run of over two hundred and fifty. Each simulation would run approximately five to ten minutes, for a total of over forty hours CPU execution time. The results of these simulations will be presented in the same order as described in the methodology. The exception to this is the angle-of-arrival experiments which will be presented jointly for both the wide and narrow band experiments. A detailed explanation and discussion of each jammer's performance will be presented as well as a comparison of the barrage and sweep jammer performance.

5.1 Wideband Experiments

To summarize the methodology presented in the preceding chapter, the wideband experiments are those that involve the use of the barrage jammer and its associated wide bandwidth. There were three experiments performed with three parameters: jammer power, jammer frequency and jammer AOA. The experiments were performed in such a manner as to hold two of the three variables constant while varying the other. This would allow conclusions to be drawn as to the effect of each parameter's variation on system performance.

5.1.1 Constant Frequency and Variable Power Case The first data collected and plotted from this case was the iterations to converge versus the signal-to-jammer ratio (SJR) of the input signal to the array. This is presented graphically in Figure 14. To explain the figure we will start from the lowest SJR to the highest. The two leftmost data points at a SJR of approximately -56 dB to -50 dB are indicative of the system adapting to the desired signal but in a manner that was quite slow in comparison to the major body of the data. These data points show the

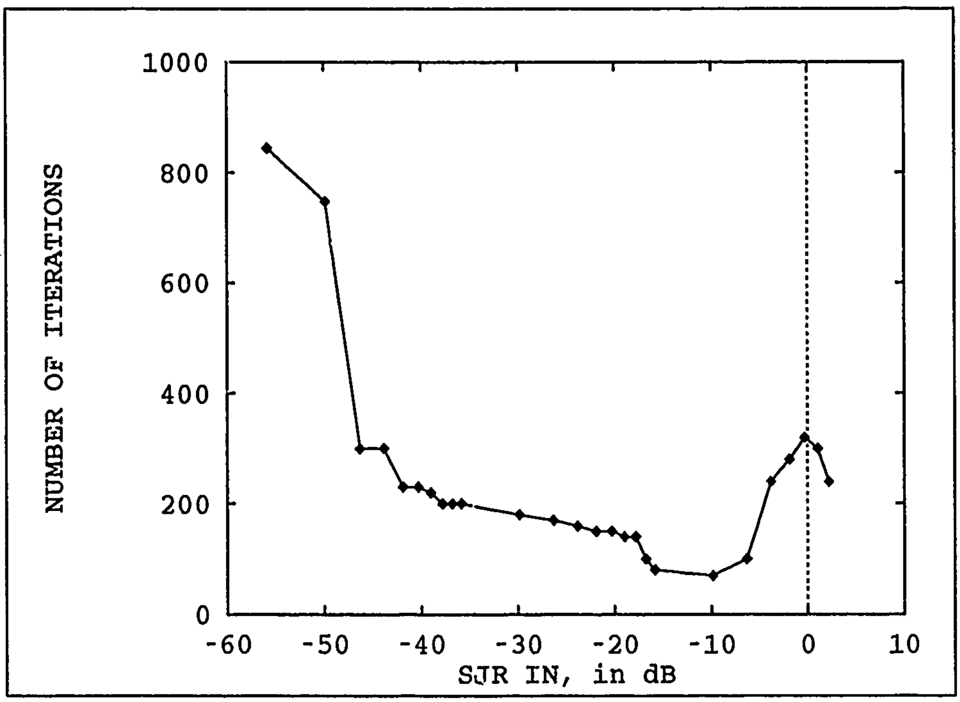


Figure 14. Barrage Jammer SJR_{in} versus Number of Iterations to Converge

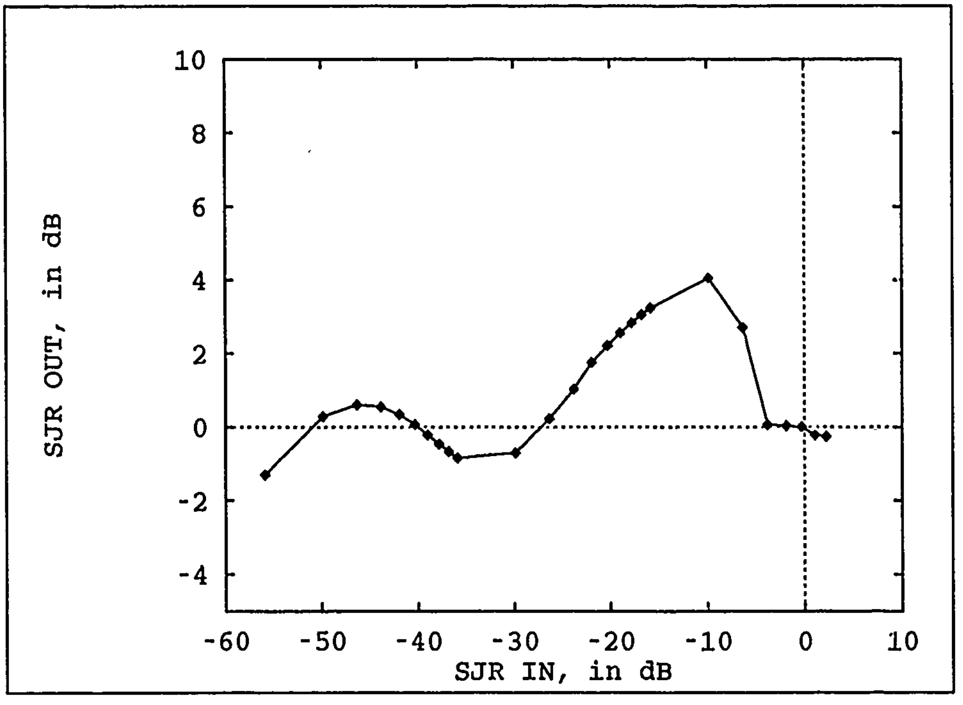


Figure 15. Barrage Jammer SJR_{in} versus SJR_{out}

typical pattern of an adaptive filter when the desired and undesired signals exceed the dynamic range of the filter. In other words, an adaptive filter can only react to signals within its dynamic range. If this is not the case, the signal strengths become too widely separated and the performance suffers. The dynamic range of an adaptive array is limited by two factors (4). The first limit is the circuitry itself. All electronic equipment has a dynamic range dependent upon the components used. This limit is not inherent to the adaptive filter itself, but to the components that are used to implement it. The second limit is the dynamic range of the adaptive filter algorithm. An adaptive filter's weight adaption is based on the eigenvalues of the input signal. When there is more than one signal present there will be eigenvalues representing each of the signals. The weights then adapt to this combination of eigenvalues. If both a strong and a weak signal are present, then the weights must attempt to adapt to an average of the different eigenvalues. The speed of response of the filter then becomes constrained. The adaptive filter cannot react to both without a loss in system performance. The other point of interest in the figure is that once the system reaches a point of normal operation (above -46 dB) an area of poor performance occurs around the SJR_{in} of 0 dB. This is due the array becoming slightly confused as to which signal is the jammer. In most situations the jammer is the signal with the most power at the input to the receiver.

The performance of the barrage jammer was consistent with that developed by Gupta (8). The plot of SJR_{in} versus SJR_{out} given in Figure 15 compared favorably with Gupta's data. As was already discussed one of the inherent limitations of the LMS adaptive array is its relatively moderate dynamic range. In this case dynamic range was -56 dB before the signal was significantly degraded. It should be noted that the poorest operating performance of the system occurred at a SJR_{in} of from -36 dB to -30 dB. Even though the performance is still within the detectable range of most receivers, it represents the local minima of the operating region. This decline in SJR_{out} was also noted by Gupta. His data revealed that it occurred at -20 dB. The difference is within acceptable limits given that the exact conditions of his experimentation are not known. The exact point of this depression is determined by the bandwidth of the noise source. The wider the bandwidth, the lower will be the point of its occurrence. The plot of data that is given is of the same general shape as that obtained by Gupta. The SJR_{out} is relatively flat over the operating range of the filter. It varies from -1 dB to 4 dB. The experiment was concluded at an SJR_{in} of 4 dB. This is the point where the SJR_{in} was better than the SJR_{out}. It would be prudent at this point in the systems operation to turn the adaptive array off and receive directly. The system loss that the array inserts at a SJR_{in} greater than 0 dB is caused by the filters dependence on the power of the desired signal model (15). This is an inverse relationship, in that the larger the desired signal model, the smaller the output signal power. This is due to the desired signal model undergoing power inversion also.

The plot in Figure 14 shows that after the SJR_{in} reaches -46 dB the iterations to converge increase rapidly with any increase in jammer power. This reflects the system being able to converge to an optimal solution but having to take more time to do it. That is not reflected in the Figure 15 since the SJR_{out} is a time average power over the life of the simulation. It can be also noted that over the operating range of the filter ($SJR_{in} >$ -56 dB) another point of poor relative performance is centered around 0 dB. At this point the filter has difficulty distinguishing between the desired signal and the undesired. It is still able to perform the nulling of the undesired signal but it takes more time to distinguish it when the power levels are equal. This would imply that there are two power levels that would be desirable from the jammers point of view. Either a very large setting in order to constrain the array or match the signal power at the point of reception is desirable, from the jammers point of view. The second option would be difficult to implement since it could be ambiguous at what power output by the jammer would be equal to the desired signal at the receiver.

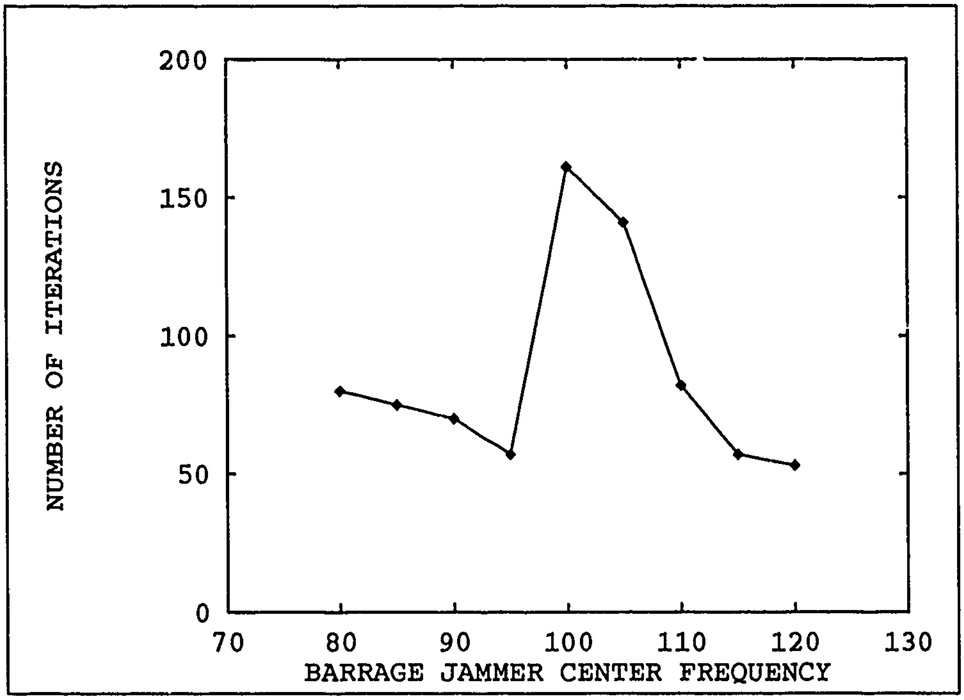


Figure 16. Barrage Jammer Center Frequency versus Number of Iterations to Converge

5.1.2 Variable Frequency and Constant Power Case The first data that was collected and plotted from this case was the iterations to converge versus the jammer center frequency as a function of transmitter frequency. This is displayed in Figure 17. As the center frequency of the jammer approaches the transmitter center frequency the performance of the system degrades. This is also shown in Figure 16, the plot of the SJR_{out} versus the jammer center frequency. This would make sense if we consider that as the center frequency of the jammer approaches the carrier frequency, more of the jammer power spectrum will be within the passband of the LMS loop. As the center frequency is moved away, less and less power is left for the system to deal with and it is more effective against the remaining power spectrum. From these plots it would be reasonable to conclude that if only a five percent difference in center frequencies can be achieved, it results in marked system performance improvement.

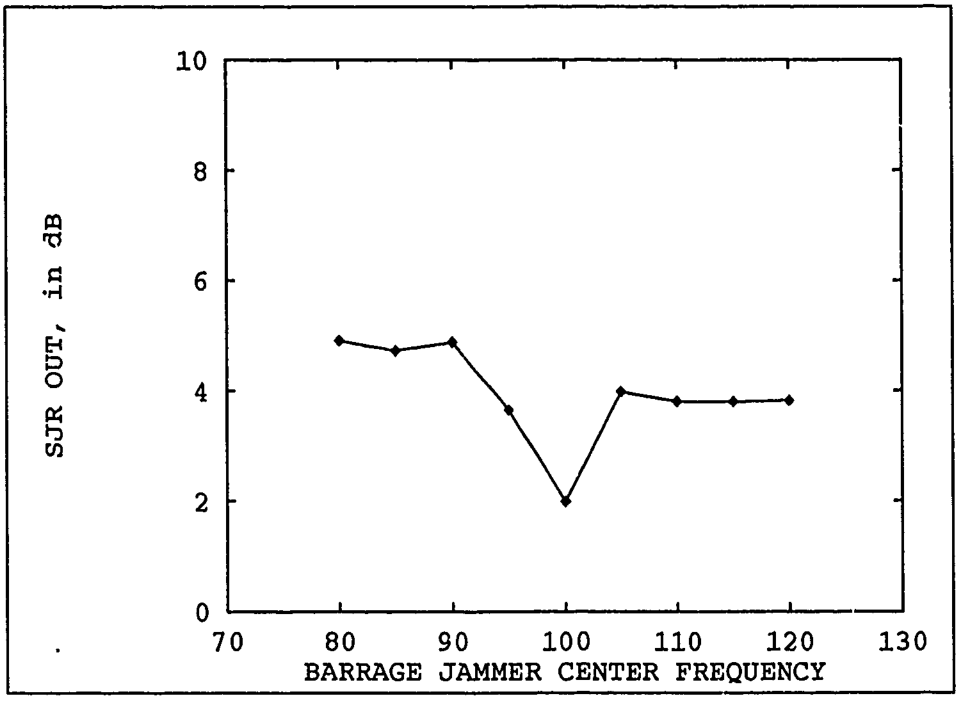


Figure 17. Barrage Jammer Center Frequency versus SJR_{out}

From the data gathered in the constant power, variable frequency experiment, any jammer frequency other than that centered on the transmitting frequency of the signal you wish to receive is preferable, from the receivers point of view. A SJR_{out} improvement of 2 dB is achieved by moving the center frequency just five percent from the jammer center frequency. This makes sense considering that the jammers output is band limited to ten percent of its center frequency. A shift of a few percent of the center frequency removes a significant portion of the jammers power spectrum from the receiver passband. It also appears that there is a slight advantage to moving the frequency lower rather than higher. It is not known why the performance of the lower frequencies was better than those of the higher at this time.

5.1.3 Summary of Wideband Experiments In general, we can conclude that the LMS adaptive array was effective against the barrage or wideband jammer. However, the wideband jammer presents a difficult challenge to the adaptive array. Wideband noise signals have frequency components that have random amplitude and phase at all points in its spectrum. When an adaptive array forms a null at a certain frequency, the wideband jammer is still corrupting the desired signal at another frequency in the receiver bandpass. To counteract this effect there are two general techniques which can be used. The first is to add more antenna elements and their coincident LMS loops. This allows for more degrees of freedom for the adaptive array. If a particular jammer is being too effective, the system can place another null on the existing one in order to combat this. This can be done over and over until the system reaches the limit of its degrees of freedom, which is constrained to $N-1$ nulls where N is the number of antenna elements. The second technique calls for additional taps to be added in series to the existing array (11). The single tap quadrature processing scheme that was used in this experiment is frequency independent. If additional taps are added the transfer function of the array then becomes frequency dependent. It can therefore track the random energy of the wideband jammer through its passband and create several nulls at various frequencies to counter the wide band effects of the

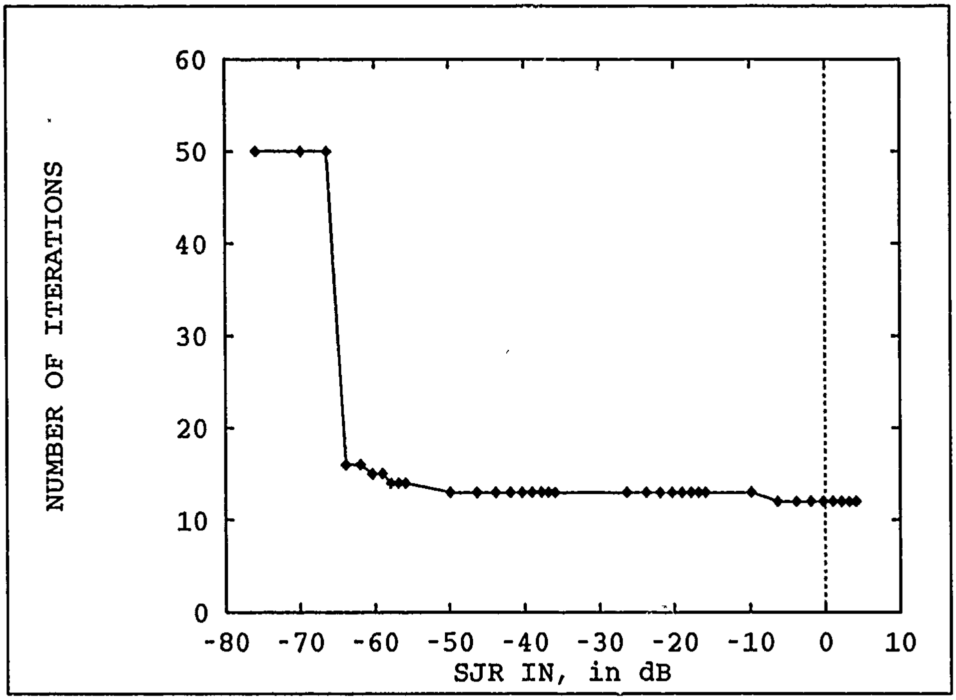


Figure 18. Sweep Jammer SJR_{in} versus Number of Iterations to Converge

barrage jammer. A three tap processor can readily handle a forty percent bandwidth jammer in this manner (11).

5.2 Narrowband Experiments

To summarize the methodology presented in the preceding chapter, the narrowband experiments are those that involve the use of the sweep jammer. There were experiments performed with three parameters of iteration: jammer power, jammer sweep rate and jammer AOA. They were performed in such a manner as to hold two of the three variables constant while varying the other. This would allow conclusions to be drawn as to the effect of each parameter on system performance.

5.2.1 Constant Sweep Frequency and Variable Power Case The data that was collected for this case in presented graphically in Figures 18 and 19. The data was collected and presented in the same manner as in the wideband variable

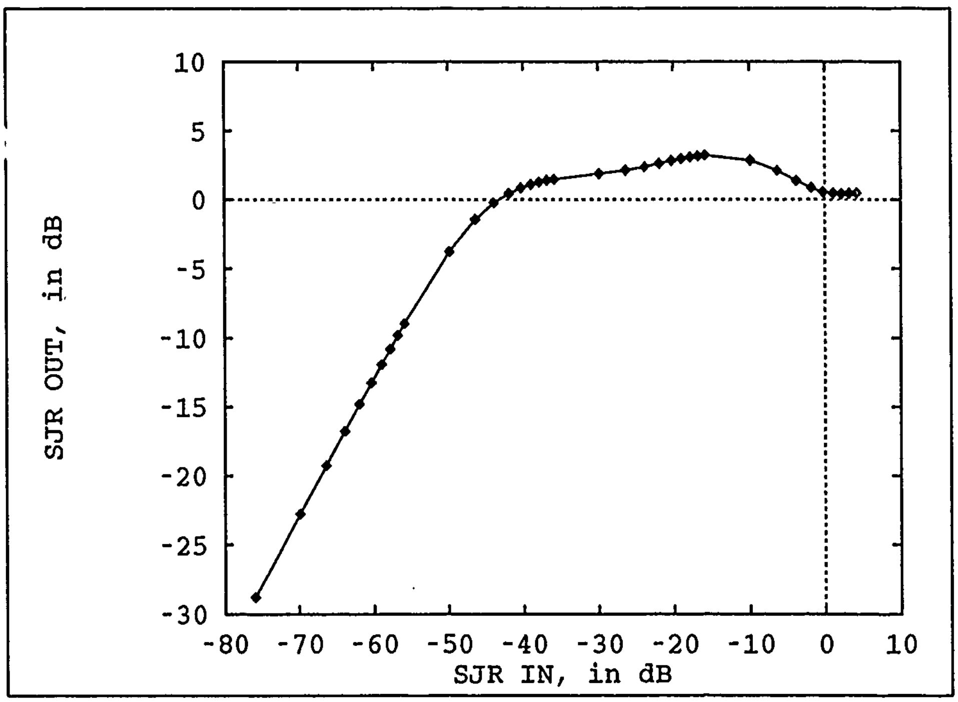
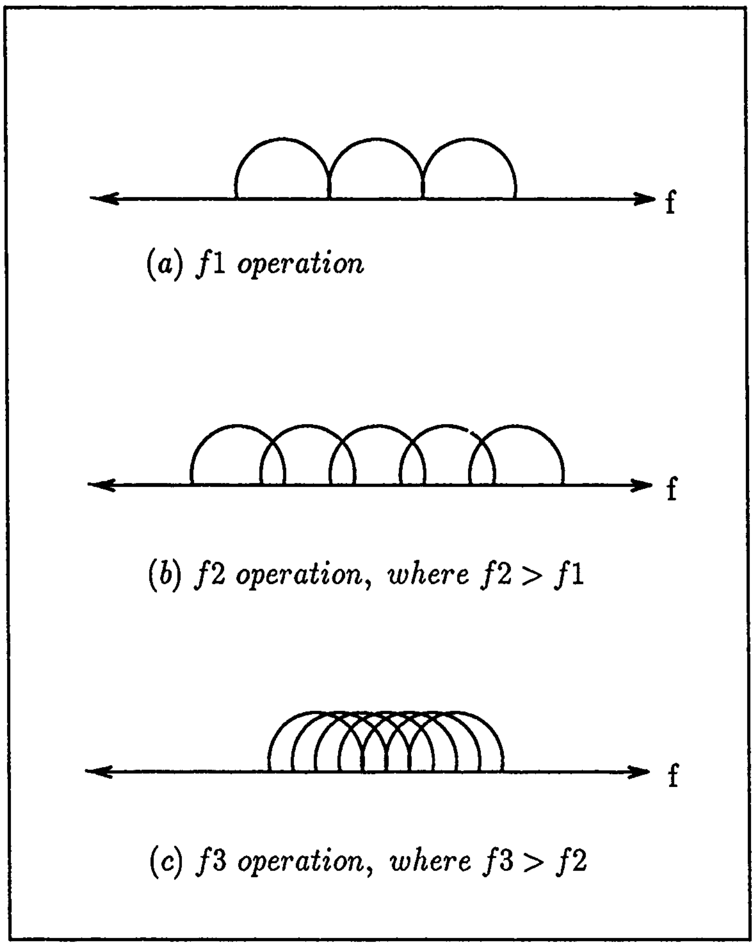


Figure 19. Sweep Jammer SJR_{in} versus SJR_{out}

power case to facilitate comparison of the two jammers effectiveness. In Figure 18 the iterations to converge versus the input SJR is shown. The value of 50 was used to represent the region were no convergence was achieved. This occurred when the SJR_{in} power level exceeded -65 dB. The remainder of the plot indicates a remarkably consistent performance for all power levels encountered. The plot of SJR_{in} versus SJR_{out} is shown in Figure 19. It shows a more graceful degradation of the SJR_{out} as the SJR_{in} increases. The system output was demodulated through a envelope detector. The demodulated output of the system was detectable at a SJR_{out} of -20 dB. The SJR_{out} can be this low with the sweep jammer due to its time varying nature. Since the jammer is constantly changing the position of its spectrum, the time that it is actually on position to jam is relatively small.

5.2.2 Variable Sweep Frequency and Constant Power Case The data collected from this case is inconclusive as to the effect of sweep rate upon the adaptive filter. As the sweep rate was gradually increased from ten to one hundred percent of the modulation frequency there was no appreciable change in system performance. It was at first interpreted as the ability of the adaptive array to track the sweep jammer through its constant sweep. This is as yet not proven or disproven. Further analysis of the spectrum of the sweep jammer was then conducted and another more plausible explanation was formed. As the sweep rate of the jammer is increased, its spectrum at each sampling time appears to overlap as in Figure 20. As this sweep rate is further increased it takes on the appearances of the spectrum of a constant amplitude tone jammer with its characteristic flat power spectrum over the frequency range. This analysis then suggests that the adaptive array is indeed immune to the effects of the sweep rate.

5.2.3 Conclusions on Narrowband Experiments The data gathered in the narrowband experiments is presented in Figures 18 and 19. From these plots the performance of the LMS adaptive array against a sweep jammer can be inferred.



(a) $f1$ *operation*

(b) $f2$ *operation, where* $f2 > f1$

(c) $f3$ *operation, where* $f3 > f2$

Figure 20. Sweep Jammer Spectrum

The plot of the iterations to converge versus SJR_{in}, shown in Figure 18, displays an almost binary response to the jammer. Either the system worked well or not at all. If the jammer power was increased so that the SJR_{in} was below -65 dB, the filter would not converge. If the power was decreased then it would converge at essentially the same rate for all power levels encountered. This implies a immunity to the power used in the sweep jammer as long as it is within the dynamic range of the filter. As is readily seen from the plot that dynamic range is -65 dB. The data gathered from the SJR_{in} versus SJR_{out} plot is a little more graceful in its degradation due to jammer power increases. The SJR_{out} was not so binary in its response. The SJR_{out} did flatten to a constant 2 dB above a SJR_{in} of -46 dB. As with the barrage jammer the filter did have a system loss after the SJR_{in} rose above 0 dB. This can be countered in a like manner as the barrage jammer by turning the adaptive array off at this point and directly receiving the signal.

5.3 Angle-of-Arrival Experiments

The angle-of-arrival (AOA) experiments for both the wide and narrow band cases displayed no significant change in system performance as a function of the AOA. There are three contributing factors to these results. The first factor is the resolution of the antenna element model. The antenna element model was described in detail in Chapter III, Implementation. The description noted that the AOA was determined by the mathematical relationship given by Eq (28) that is a function of the operating frequency, the sample time and the phase delay. At the low frequencies that were used for these simulations the minimum AOA separation between two signals is six degrees. The separation between the main beam of the array and an adjacent null could be easily contained in this six degrees. Any further separation would only slightly increase the depth of the null and its consequent performance. The second factor is that the noise jammers and the modulated data are of a highly uncorrelated nature. Since the received signals were highly uncorrelated with each other any additional phase shift between the noise jammer and the modulated data signal would not add much more discrimination for the filter to use. The third factor is that a quadrature hybrid receiving system was used. The quadrature hybrid single-tap filter that was implemented in these experiments has a time-varying response that is a function of μ. The value of μ adapts to the changing input signal strength. When a signal arrives at a angle other than the boresight of the antenna, there is a phase difference between each element of the antenna. Since each element and its quadrature had its own independent adaptive filter and corresponding value of μ, this phase shift did not change the input signal autocorrelation or crosscorrelation functions that the LMS depends on for its adaptation. Since no change was made to the input correlation or crosscorrelation matrices there was no change in the system performance. Therefore the experiment produced the results that were to be expected for a system that produced the null separation and employed highly uncorrelated input signals with quadrature processing. These results pertaining to AOA experiments may not be applicable to other types of modulation types and processing, and in fact for most systems, the AOA is a very important aspect of the input signals.

VI. Conclusions and Recommendations

This chapter will summarize the results presented in Chapter V and draw conclusions based on those results. The conclusions will discuss the effectiveness of the LMS adaptive array in the presence of the individual barrage and sweep jammers. In addition, recommendations will be made concerning further areas of research that may be undertaken in pursuit of this topic.

6.1 Conclusions

The LMS algorithm appeared to be effective against the barrage jammer. That effectiveness could be improved if the complexity of the adaptive array were increased by the addition of more LMS loops in either parallel or series. The arrays best performance occurred at -10 dB, while its worst (within operating dynamic range) occurred at -30 dB. These values are consistent with other research and are determined on the curve by the bandwidth of the jammer. A jammer with a different bandwidth will exhibit the same general curve shape with these minima and maxima occurring at different values of SJR_{in}. The array can be confused by the appearance of signals at the input with the same power levels and it will take longer to determine the desired signal. The SJR_{out} may be improved by a reduction in the power of the desired signal model. There are trade-offs to be considered and limitations to this improvement that are not addressed in this document. It is detrimental to have the transmitting signal center frequency to be at the center frequency of the barrage jammer. A difference of five percent results in at least a 3 dB improvement in SJR_{out}.

The performance of the LMS adaptive array against the sweep jammer was also quite impressive. The system had an essentially constant response that was independent of the SJR_{in}, so long as that value was within the dynamic range of the array. When the dynamic range was exceeded there was a sharp drop-off in performance. There was no convergence within the length of the simulation in this area but the SJR_{out} did appear to degrade more gracefully. The array exhibited an immunity to the sweep rate of the jammer.

6.2 Recommendations

The primary goal of this thesis effort was to document the effectiveness of the LMS algorithm in an adaptive array against jammers that are typically encountered in a combat environment. The research that is contained in this document is far from complete in its treatment of the problem of interference suppression. There are other areas that are in need of further exploration and this section will document some of those general directions that may be undertaken in other research efforts. In addition the use of BOSS as a simulation environment will be discussed.

6.2.1 Recommendations for Further Research The first recommendation concerns the types of signals used and various combinations of them. The performance of the LMS adaptive array is directly proportional to the correlation between the interference and the desired signal. It therefore becomes necessary to document the performance of the array using various forms of modulation (i.e. NBFM, WBFM, FSK, QPSK, etc) against the known jammer types. There are also spread spectrum techniques that may impose some constraints on the usage of adaptive arrays that are not obvious. It would also be interesting to determine the effects a combination of jammers might have. Do three jammers with a given output power of X dB have the same effect as a single jammer with the same output power? The jammers that were used were by far the most common but there exist a myriad of more exotic and modern methods for signal interference that require evaluation.

The second recommendation concerns the antenna array elements. The use of ideal omnidirectional antenna elements is useful in isolation of the performance of a particular portion of a receiver system, such as the adaptive array. In a situation where it is required to simulate the performance of an adaptive array with a particular geometry and element pattern, a more complex simulation is needed. A method for inputting that array geometry and pattern is required. This is quite feasible using the BOSS environment of parameter input. These first two recommendations were also recommended by Srubar (10) and are expounded on here.

The third recommendation concerns the adaptive array techniques to suppress wide band or multiple jammers. The use of N antenna elements to create $N-1$ nulls was discussed as a method to combat this particular threat. It has also been proposed that an array with several taps on each element would be effective against wide band or multiple threats (8). A effort to quantitatively document that effectiveness would be of interest.

The fourth recommendation concerns the optimization of the desired signal model. This may be the most interesting topic that is recommended and little is published concerning the modeling techniques and how to optimize them. There are two major types of information (digital and analog or voice) used with countless modulation types. The question is, how do you know what model optimizes your signal out of the adaptive array? It is desired that the signal model be highly correlated with the desired signal while uncorrelated with the interference. What is the trade-off between the two? Is it more desirous to be more correlated with the desired signal at the expense of being less uncorrelated with the interference?

The final recommendation that is made concerns the implementation of an adaptive beamformer using a neural network. The LMS algorithm developed by Widrow et al is a very simple form of neural network using a very simple learning method. A different and perhaps more complex neural network might be able to better adapt to complex and hostile electromagnetic environment than the LMS could. There is considerable research being done in this area and background material is readily available.

6.2.2 BOSS as a Simulation Environment The use of BOSS as a simulation environment for adaptive arrays proved successful. BOSS provided all of the primitive modules that were necessary for the construction of all the desired but more complex modules. The graphics interface to it was very helpful in easing the construction of these modules. These findings concur with those stated by Srubar (10) in his research. The only limits encountered were were with the BOSS environment interacting with the computer it was hosted on. The system that BOSS resides on had limited disk storage space and BOSS can easily consume vast quantities of disk storage while executing a simulation. This proved to be a hinderence in running simulations with normal RF frequencies and the sampling that they require. If more disk storage were available the system can produce realistic simulations of RF systems in operation. The use of BOSS is recommended for use in further research in this area.

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